Some thoughts on likelihood based/enhanced twin refinement

Peter Zwart

- Twinning is a frequently occuring phenomenon
- Standard ML target functions are inappropriate
- 6 LS target however available
- What about map coefficients?

Feedback

Data is twinned as follows:

$$J_1 = (1 - \alpha)I_1 + \alpha I_2$$

$$J_2 = (1 - \alpha)I_2 + \alpha I_1$$

6 in matrices:

$$\begin{pmatrix} J_1 \\ J_2 \end{pmatrix} = \begin{pmatrix} (1-\alpha) & \alpha \\ \alpha & (1-\alpha) \end{pmatrix} \begin{pmatrix} I_1 \\ I_2 \end{pmatrix}$$

6 Algebraic detwinning of data is straightforward

$$\begin{pmatrix} J_1 \\ I_2 \end{pmatrix} = \frac{1}{1 - 2\alpha} \begin{pmatrix} (1 - \alpha) & -\alpha \\ -\alpha & (1 - \alpha) \end{pmatrix} \begin{pmatrix} J_1 \\ J_2 \end{pmatrix}$$

- 6 Detwinning is unstable when α close to 0.5.
- 6 Detwinning not possible when α is 0.5.
- One can end up with negative intensities
- 6 What to do about experimental uncertainty?

- 6 If no experimental errors were present, twin refinement would be same as normal refinement
- 6 The trick is to introduce experimental errors in a suitbale way.
- There are two ways in which one can introduce experimental errors
- A small excursion is made to elucidate the thought process I went through myself.

A short excursion, I

- An observed intensity has an associated standard deviation
- These two numbers are usually interpreted as parameters in a (approximately) Gaussian distribution of the error free intensity

$$P(I_{\text{true}}|I_{\text{obs}}, \sigma_{\text{obs}}) = C \exp \left[-\frac{(I_{\text{true}} - I_{\text{obs}})^2}{2\sigma_{\text{obs}}^2} \right]$$

The normalisation constant C is obtained by integrating over the domain on which the random variable is defined: $[0, \infty)$

A short excursion, II

- 6 Apply transformation: $F_{
 m true}^2 = I_{
 m true}$
- 6 The associated Jacobian is : $2F_{\rm true}$
- one obtains

$$P(F_{\text{true}}|I_{\text{obs}}, \sigma_{\text{obs}}) = 2F_{\text{true}}C \exp\left[-\frac{(F_{\text{true}}^2 - I_{\text{obs}})^2}{2\sigma_{\text{obs}}^2}\right]$$

- If desired, a Gaussian distribution may be fitted to this function
- The mean of this gaussian is than equal to the maximum likelihood mestimate of $F_{\rm true}$

A short excursion, III

- ullet Call the MLE $\hat{F}_{
 m true}$
- The inverse of the square root of the negative second derivative of the log likelihood function at the MLE is equal to the standard deviation when fitting a Gaussian

$$\hat{F}_{\text{true}} = \sqrt{\frac{I_{\text{obs}}}{2} + \frac{1}{2}\sqrt{I_{\text{obs}}^2 + 2\sigma_{\text{obs}}^2}}$$

$$\sigma_{\hat{F}_{\text{true}}} = \frac{\sigma_{\text{obs}}}{2(I_{\text{obs}}^2 + 2\sigma_{\text{obs}}^2)^{1/4}}$$

A short excursion, IV

- Note that negative intensities do not form a problem
- The procedure is similar to the truncate procedure.
- Truncate uses a Wilson prior, here a uniform prior is used.
- Truncate uses mean intensity rather than maximum likelihood estimate of amplitude.
- Use the -massage-intensities option in iotbx.reflection_file_converter

A Gaussian model, I

- We will use the same approach as above, but for twinned data
- If the errors between two twin related intensities are independent, one can write

$$P(I_1, I_2) = C \exp \left[-\frac{(J_1 - I_{o1})^2}{2\sigma_1^2} - \frac{(J_2 - I_{o2})^2}{2\sigma_2^2} \right]$$

$$J_1 = (1 - \alpha)I_1 + \alpha I_2$$

$$J_2 = (1 - \alpha)I_2 + \alpha I_1$$

A Gaussian model, II

6 Convert to amplitudes

$$P(F_1, F_2) = 4F_1 F_2 C \exp \left[-\frac{(J_1 - I_{o1})^2}{2\sigma_1^2} - \frac{(J_2 - I_{o2})^2}{2\sigma_2^2} \right]$$

$$J_1 = (1 - \alpha)F_1^2 + \alpha F_2^2$$

$$J_2 = (1 - \alpha)F_2^2 + \alpha F_1^2$$

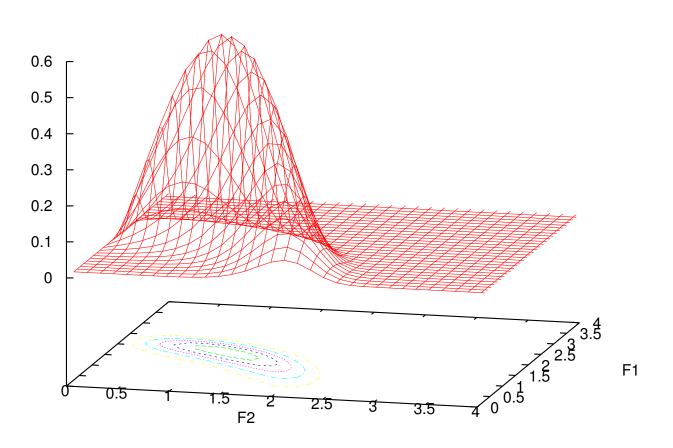
$$I_{o1} = 3.2$$

$$I_{o2} = 1.2$$

- $\sigma_{o1} = 0.8$
- $\sigma_{o2} = 0.8$
- $\alpha = 0.45$
- 6 Detwinned intensities: 1.22 & -0.78

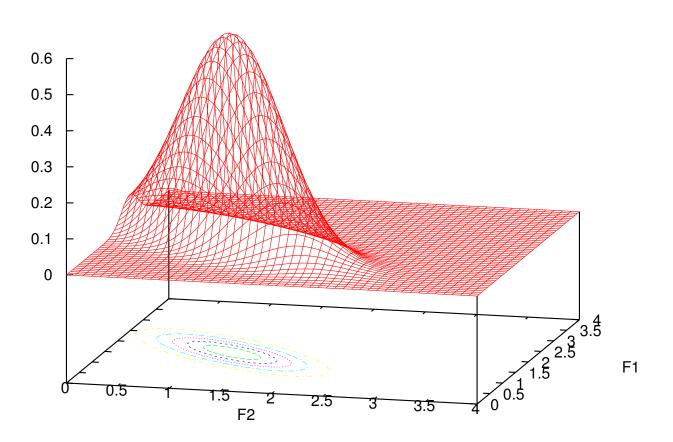


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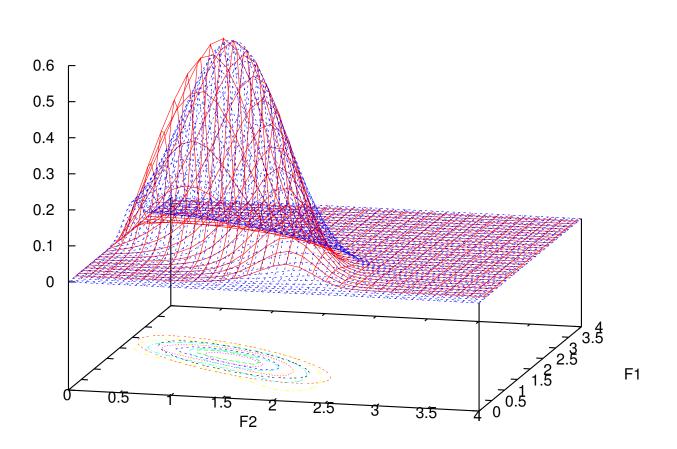


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- When things are 'nice', the MLE of a detwinned intensity pair is approximately equal to the algebraic detwinned intensities.
- No negative detwinned intensities possible
- 6 A (reasonable?) Gaussian approximation can be made.
- 6 An estimate of the variance/covariance is obtained from the derivatives of the log likelihood function in 'at the detwinned' amplitudes.

Likelihood based twin refinement

6 A likelihood funtion for twin refinement can be derived:

$$P(F_{o1}, F_{o2}) = \int_0^\infty \int_0^\infty P(F_1|F_{c1})P(F_2|F_{c2})P(F_1, F_2|F_{o1}, F_{o2})$$

- 6 This is derivation is analogous to the derivation of MLF1
- If all densities are approximated by Gaussians and the integration limits are expanded to $-\infty$, an expression in closed form is obtained.

Likelihood based twin refinement

- Gaussian approximations for $P(F_1|F_{c1})$ can be equal to the approximation made in CNS (method of moment)
- A Gaussian approximation of $P(F_1, F_2 | F_{o1}, F_{o2})$ has to be made only once for a fixed twin fraction. This can be done numerically. I wasn't able to formulate an analytic solution.

Another route

- 6 Another route can be followed to obtain a likelihood function
- 6 Get distributions in intensities: $P(F_1|F_{c1}) \rightarrow P(I_1|I_{c1})$
- 6 Introduce twinning: $P(I_1|I_{c1})P(I_2|I_{c2}) \to P(J_1J_2|I_{c1}I_{c2})$
- 6 Introduce experimental errors by a 2 d convolution.
- Various domain issues make life less simple

Map coefficients

- To compute a map, $\mathbb{E}[F_{o, \text{untwinned}}]$ is needed.
- 6 For untwinned data, this is equal to mF_o
- 6 When twinning is involved, we effectively need a detwinning step
- Currently, I use Sheldricks proportionality rule

$$F_{o1,ut}^2 = \frac{(1-\alpha)F_{c1}}{I_{c1}}I_{o1} + \frac{\alpha F_{c1}}{I_{c2}}I_{o2}$$

Map coefficients

- Not sure what the untwinned observed amplitude is
- 6 could use the expected F_c given model and observation
- 6 Use σ_A estimation on detwinned data without model info to avoid bias issues
- 6 difference maps?